Research Article

LSTM-Based Output-Constrained Adaptive Fault-Tolerant Control for Fixed-Wing UAV with High Dynamic Disturbances and Actuator Faults

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Received 15 September 2020; Revised 30 January 2021; Accepted 4 February 2021; Published 10 March 2021

Academic Editor: Adrian Neagu

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The unknown disturbances and the changing uncertainties bring difficulties for designing a stable attitude controller for UAV. In this paper, a novel adaptive fault-tolerant attitude control approach is designed based on the long short-term memory (LSTM) network for the fixed-wing UAV subject to the high dynamic disturbances and actuator faults. Firstly, the high dynamic disturbances can be compensated by the adaptive laws. Meanwhile, the actuator faults can be handled by the proposed adaptive fault-tolerant control (AFTC) scheme. Moreover, the LSTM network is introduced to approximate the unknown and time-accumulating nonlinearities. With the introduction of the one-to-one nonlinear mapping (NM), the output constraints in the control system can be guaranteed. Additionally, it can be demonstrated that the boundness of all the signals can be assured. At last, numerical simulation results are provided to illustrate the effectiveness of the proposed method.

1. Introduction

The fixed-wing UAVs are inevitable and useful in many fields [1]. Especially, in the military, they show an indispensable position in the modern battle fields with their advantages of strong penetration, strong mobility, and good concealment [2]. There is no doubt that the attitude control of UAVs directly affects whether they can move as expected. The main challenge for the attitude control of fixed-wing UAVs results from their strong coupling, strong nonlinearity, and parameter uncertainties. Moreover, in the actual flight mission, the attitude of the fixed-wing UAVs tends to be affected by the complex environment and the variable terrain or even encounters the actuator faults. Therefore, the above reasons drive the controller design difficulties to a higher degree and how to tackle such a daunting challenge has attracted significant attention in recent years. In the past decades, several advanced control methods for UAVs have been investigated, such as PID control [3, 4], backstepping

control [5], sliding mode control [6, 7], and other classical or modern control theories and methods [8, 9]. To be more specific, in literature [10], Li and his colleagues have proposed an adaptive PID control method, which introduced multivariable neural network based on radial basis function (RBF), for UAVs with the high nonlinear and strong coupling. Moreover, an adaptive backstepping control approach is designed for trajectory tracking of quadrotor UAV [11]. Furthermore, in [5], in order to make the control systems more robust, a novel integral backstepping controller is proposed for UAVs. A first-order sliding mode controller combined with the backstepping theory has been employed in [12], and it achieved a satisfactory performance for the UAVs' attitude control. In order to reduce the chattering phenomenon, literature [13] has investigated the second-order sliding mode technique for attitude tracking of an unmanned aircraft system (UAS) and verified the superiority of the proposed method compared with the first-order sliding mode method.

It should be noticed that the aforementioned literatures focus on the attitude control without taking the high dynamic disturbances and time-varying uncertainties into consideration, which have to be handled to guarantee the accuracy of the tracking performance. At present, domestic and foreign researchers put forward various control methods to cope with ant disturbance and disturbance attenuation, such as adaptive backstepping control [14], disturbance observer-based control (DOBC) [15–17], adaptive sliding mode control (ASMC) [18–20], and active disturbance rejection control (ADRC) [21, 22]. Literature [23] has introduced the adaptive backstepping control strategy to compensate the lumped disturbance term for a quadrotor UAV. In the presence of model parameter uncertainty, literature [24] designed a robust trajectory tracking control law based on DOBC, which is used to estimate the unknown terms. To reduce the complexity of system design, Zhang and his colleagues proposed an ASMC method, without using disturbance observer, to design the attitude controller for the fixed-wing UAV with external disturbances [25]. A classical ADRC method and another combined ADRC method with SMC are proposed in [26, 27] for UAVs with the parametric uncertainties and external disturbances, and it can be verified that the performance of the latter is better by comparison. But none of the aforementioned methods mentioned the suppression of the time-varying disturbances. Further, literatures [28, 29] have handled the time-varying disturbances with backstepping algorithm and SMC separately, but the changing rate of disturbances is not high. Therefore, the above research studies cannot efficiently deal with the high dynamic disturbances for UAVs.

It is worth mentioning that the actuator faults are unavoidable for unmanned aerial vehicles (UAVs) in the actual control systems, which can degrade the control performance. Recently, research studies on real-time fault diagnosis are considered to improve the accuracy of fault prediction and the stability of flight, and they can also reduce the risk of task interruption caused by faults. Quan and his colleagues [30] have devised a fault diagnosis scheme based on the neural network sliding mode observer; however, it can only handle with the minor fault. In addition, the diagnosis scheme based on unknown input observer is exploited in [31], which can dispose the situation more closer to the actual flight for quadrotor UAVs. Furthermore, for different fault scenarios, Zhong et al. [32] designed a robust control scheme merging the fault detection with diagnosis. However, with the existence of actuator faults, the fault-tolerant control (FTC) is one of the valid control methods to maintain normal operation applied to the flight of UAV. In practical application, plentiful papers have investigated FTC for UAV with actuator fault. Literatures [33, 34] have designed the fault-tolerant controller for single UAV and multi-UAVs with actuator faults, respectively. Xing et al. [35] compared the AFTC method with the passive fault-tolerant control (PFTC) method, who demonstrated that the former has a stronger fault tolerance performance. Following that, aiming for better stability and stronger fault-

tolerant capability, a surge of research studies has been devoted to the active fault-tolerant control (AFTC) method. The literature [36] investigates the improved adaptive fault-tolerant H-infinity control scheme to develop the tracking properties of formation flight with unknown multiplicate actuator fault. Further, without the need of control reconfiguration, Abbaspour et al. [37] designed a neural network-based AFTC scheme to detect and isolate the faults in real time.

In recent years, intelligent theories and methods have developed rapidly, providing a convenient and reliable way to approximate and compensate the uncertainty and unknown nonlinearity in the control system. As we all know, radial basis function neural network (RBFNN) [38, 39] is the common approximation method. In order to cope with time-varying nonlinearity, RBFNN has been mentioned in [40–42] for approximation and compensation. However, in the actual flight control of UAVs, the nonlinear terms possess time-varying accumulative effect. Therefore, an intelligent theory with memory function needs to be proposed to solve this problem so as to ensure better tracking performance of the control system. The concept of LSTM network has been proposed for the first time in [43] for the noisy and other disturbances, which possesses the storage and memory functions. Literatures [44, 45] have verified the applicability and effectiveness of LSTM prediction model in practical application. Moreover, literature [43] has introduced LSTM to investigate trajectory prediction. Very recently, in reference [46], an intelligent LSTM controller is designed to improve the control accuracy and stability, and the performance test shows that the prediction accuracy with RBFNN is lower than that of the LSTM method. However, the approach in [46] is limited to the theoretical perspective. Unfortunately, to the best of the authors' knowledge, few research studies report the attitude control schemes based on LSTM network for the fixed-wing UAVs. Not only that, there are also very few results devoted to the AFTC based on LSTM and the disturbance suppression methods to deal with the high dynamic disturbances for UAVs. Furthermore, in the presence of high dynamic disturbances, how to guarantee the output constraints of LSTM-based AFTC for UAVs is still a blank.

Motivated by the observation above, a LSTM-based nonlinear output-constrained adaptive fault-tolerant controller is designed for 6-DOF fixed-wing UAV with high dynamic disturbances and actuator faults. Compared with the existing results, the main contributions of this paper are as follows:

- (i) To the best of the authors' knowledge, this is the first paper introducing LSTM network to handle the disturbance suppression problems for the fixed-wing UAVs' attitude controller design.
- (ii) The LSTM-based adaptive fault-tolerant attitude controller is developed for the fixed-wing UAVs subject to the high dynamic disturbances and actuator faults in this paper. Meanwhile, the output constraints can be guaranteed and the tracking

errors of the attitude angles can also be bounded in the predefined boundaries.

- (iii) The proposed method in this paper has a small amount of computation. Meanwhile, it can reduce the complexity of the controller and has a good control performance; therefore, it can be extended to solve other nonlinear higher disturbances problems.

2. Problem Formulation and Preliminaries

2.1. Fixed-Wing UAV Modeling. According to literature [47], the kinematic and dynamic equations of fixed-wing UAV can be established as follows:

$$\begin{cases} \dot{\vartheta} = \omega_y \sin \gamma + \omega_z \cos \gamma, \\ \dot{\psi} = \frac{(\omega_y \cos \gamma - \omega_z \sin \gamma)}{\cos \vartheta}, \\ \dot{\gamma} = \omega_x - \tan \vartheta (\omega_y \cos \gamma - \omega_z \sin \gamma), \\ \dot{\omega} = I^{-1} [M - \omega \times (I \cdot \omega)], \end{cases} \quad (1)$$

where ϑ, ψ , and γ are the pitch angle, yaw angle, and roll angle, respectively, $\omega = [\omega_z \ \omega_y \ \omega_x]^T$ represents the attitude angular velocity vector, which is composed of the yaw, pitch, and roll angular rates, I is the rotational inertia matrix of UAV, and M is the torque applied to the center of mass of UAV; their matrix forms can be expressed as

$$\begin{aligned} I &= \begin{bmatrix} I_{xx} & 0 & I_{xz} \\ 0 & I_{yy} & 0 \\ I_{zx} & 0 & I_{zz} \end{bmatrix}, \\ M &= qSL \begin{bmatrix} C_z \\ C_y \\ C_x \end{bmatrix}, \end{aligned} \quad (2)$$

where $I_{\Delta\Delta}$ is the product of inertia in two directions, $q = (\rho V^2/2)$ is the dynamic pressure, ρ is the atmospheric density, V is the flying speed of UAV, S is the wing area, $L = \text{Diag}[c, b, b]$, c is the average chord length, and b is the wingspan. Moreover, C_z, C_y, C_x are the main control factors of pitch torque, yaw torque, and roll torque, respectively, which can be expressed as

$$\begin{cases} C_z = C_{z0} + C_z^{\delta_{a1}} \delta_{a1} + C_z^{\delta_{a2}} \delta_{a2} + C_z^{\delta_{b1}} \delta_{b1} + C_z^{\delta_{b2}} \delta_{b2} + C_z^{\alpha} \alpha, \\ C_y = C_y^{\delta_y} \delta_y + C_y^{\beta} \beta, \\ C_x = C_x^{\delta_{a1}} \delta_{a1} + C_x^{\delta_{a2}} \delta_{a2} + C_x^{\delta_{b1}} \delta_{b1} + C_x^{\delta_{b2}} \delta_{b2} + C_x^{\beta} \beta, \end{cases} \quad (3)$$

where δ_{a1}, δ_{a2} are rudder deviation of left and right ailerons, respectively, δ_{b1}, δ_{b2} are the rudder deviations of left and

right lifting wings, respectively, δ_y is the rudder deviation of directional wing, and α, β are angle of attack and sideslip, respectively, which can be calculated by the following formula:

$$\begin{cases} \dot{\alpha} = \omega_z + \frac{\rho V S C_{z\alpha}}{2m} \alpha, \\ \dot{\beta} = -\omega_y + \frac{\rho V S C_{y\beta}}{2m} \beta, \end{cases} \quad (4)$$

where C_{z0} is the pitch torque coefficient when $\delta_{a1} = \delta_{a2} = \delta_{b1} = \delta_{b2} = \alpha = 0$, C_{Δ}^{Δ} is the derivative of the coefficient of aerodynamic torque to the corresponding angle, and $C_{z\alpha}, C_{y\beta}$ are derivatives of the aerodynamic torque coefficients to the angle of attack and sideslip, respectively.

Define $\theta = [\vartheta \ \psi \ \gamma]^T$, $\omega = [\omega_z \ \omega_y \ \omega_x]^T$, and $\delta = [\delta_{b1} \ \delta_{b2} \ \delta_y \ \delta_{a1} \ \delta_{a2}]^T$; then, the attitude dynamic equation of the UAV system can be described as

$$\begin{aligned} \dot{\theta} &= A_{\theta} \omega + d_{\theta}(t), \\ \dot{\omega} &= B_{\omega} \delta + C(\omega) + d_{\omega}(t), \end{aligned} \quad (5)$$

where $d_{\theta}(t), d_{\omega}(t) \in \mathbb{R}^{3 \times 1}$ represent the disturbances in the attitude angle dynamics and attitude angular velocity dynamics, respectively. $A_{\theta} \in \mathbb{R}^{3 \times 3}, B_{\omega} \in \mathbb{R}^{3 \times 5}, C(\omega) \in \mathbb{R}^{3 \times 1}$ are expressed as

$$A_{\theta} = \begin{bmatrix} \cos \gamma & \sin \gamma & 0 \\ -\frac{\sin \gamma}{\cos \vartheta} & \frac{\cos \gamma}{\cos \vartheta} & 0 \\ \tan \vartheta \sin \gamma & -\tan \vartheta \cos \gamma & 1 \end{bmatrix},$$

$$B_{\omega} = \kappa C_M,$$

$$C(\omega) = I^{-1} \left\{ qSL \begin{bmatrix} C_{z0} + C_z^{\alpha} \alpha \\ C_y^{\beta} \beta \\ C_x^{\beta} \beta \end{bmatrix} + \begin{bmatrix} \omega_z \\ \omega_y \\ \omega_x \end{bmatrix} \times \left(I \begin{bmatrix} \omega_z \\ \omega_y \\ \omega_x \end{bmatrix} \right) \right\}, \quad (6)$$

where

$$\begin{aligned} \kappa &= qSLI^{-1}, \\ C_M &= \begin{bmatrix} C_z^{\delta_{b1}} & C_z^{\delta_{b2}} & 0 & C_z^{\delta_{a1}} & C_z^{\delta_{a2}} \\ 0 & 0 & C_y^{\delta_y} & 0 & 0 \\ C_x^{\delta_{b1}} & C_x^{\delta_{b2}} & 0 & C_x^{\delta_{a1}} & C_x^{\delta_{a2}} \end{bmatrix}. \end{aligned} \quad (7)$$

In practice, there often exist structural uncertainties and modeling errors. Therefore, considering these factors, we can rewrite (5) as

$$\begin{aligned}\dot{\theta} &= [A_\theta + \Delta A_\theta]\omega + f(\theta) + d_\theta(t), \\ \dot{\omega} &= [B_\omega + \Delta B_\omega]\delta + C(\omega) + f(\theta, \omega) + d_\omega(t),\end{aligned}\quad (8)$$

where ΔA_θ represents the structural uncertainties of A_θ , and let $f(\theta)$, $f(\theta, \omega)$ represent the unknown lumped aerodynamic uncertainties. ΔB_ω represents the composite uncertainties caused by modeling errors and aerodynamic perturbations of B_ω , which is expressed as

$$\Delta B_\omega = \Delta\kappa \cdot C_M + \kappa \cdot \Delta C_M, \quad (9)$$

where $\Delta\kappa$ represents the uncertainties of κ .

Therefore, the aim of this paper is to design a control law δ , which forces the attitude angle to follow the desired commands in the presence of the actuator faults and the composite disturbances of the structural uncertainties and the aerodynamic uncertainties for the fixed-wing UAVs.

Remark 1. In fact, it is essential to take changing actuator faults and high dynamic disturbances into consideration, which are difficult to be dealt with and also challenging for the attitude controller design. However, the existing control methods without considering these factors cannot guarantee the stability of the systems. That is to say, in practice, once we ignore their effects, the control system tends to be unstable or even diverges, which leads to serious consequences, such as flight mission failure or even aircraft damage.

2.2. Supporting Assumptions and Lemma. For the concerned system, the following assumptions and lemma are made.

Assumption 1. The coefficient matrix $A_\theta \in \mathbb{R}^{3 \times 3}$ is invertible and the long square matrix $B_\omega \in \mathbb{R}^{3 \times 5}$ is generalized invertible, that is, $\det(BB^T) \neq 0$.

Assumption 2. The desired attitude signal $\theta_d = [\vartheta_d, \psi_d, \gamma_d]^T$ is twice differentiable and continuous bounded.

Assumption 3. It is supposed that the disturbances $d_\theta(t)$, $d_\omega(t)$ are bounded signals, e.g., $\|d_\theta(t)\| \leq \bar{D}_\theta$, $\|d_\omega(t)\| \leq \bar{D}_\omega$, where $\bar{D}_\theta, \bar{D}_\omega$ are unknown positive constants.

Assumption 4. $\text{rank}(A_\theta, \Delta A_\theta) = \text{rank}(A_\theta) = 3$.

Assumption 5. It is assumed that the uncertainties of A_θ, B_ω cannot change the control directions, that is, $\lambda_{\min}(\Omega_\theta) > 0$ and $\lambda_{\min}(\Omega_\omega) > 0$, where $\Omega_\theta = ((A_\theta + \Delta A_\theta)/A_\theta)$ and $\Omega_\omega = ((B_\omega + \Delta B_\omega)/B_\omega)$.

In order to facilitate the subsequent stability analysis, it is necessary to introduce the following lemma.

Lemma 1 (see [40]). Define any positive number $\chi_\varepsilon > 0$ and any variable $z \in \mathbb{R}$; it satisfies the following inequality:

$$0 < \|z\| - \frac{z^T z}{\sqrt{z^T z} + \chi_\varepsilon} < \chi_\varepsilon. \quad (10)$$

2.3. Long Short-Term Memory Network Approximation. In this paper, LSTM networks are employed to approximate the unknown nonlinearities. The main idea of this concept is that there are both immediate input states, as well as the long-term storage states and the short-term storage states reserved at the previous level when states are transferred between multiple levels. Among them, the unit of long-term storage state is called the central node, and then the weight is used to reflect the importance of each state in the output. The concept of “gate” is introduced in LSTM, that is, its principle is illustrated by the concepts of forget gate, input gate, update gate, and output gate. The structure of LSTM network is presented Figure 1.

The mathematical expression of forget gate, input gate, memory state, update gate, and output gate can be depicted in the following forms, respectively.

$$\begin{aligned}f_t &= \sigma(W_f[h_{t-1}, x_t] + b_f), \\ i_t &= \sigma(W_i[h_{t-1}, x_t] + b_i), \\ \tilde{c}_t &= \tanh(W_c[h_{t-1}, x_t] + b_c), \\ c_t &= f_t \circ c_{t-1} + i_t \circ \tilde{c}_t, \\ o_t &= \sigma(W_o[h_{t-1}, x_t] + b_o).\end{aligned}\quad (11)$$

Meanwhile, h_t represents the hidden layer output state, that is,

$$h_t = o_t^\circ \tanh(c_t), \quad (12)$$

where W_f, W_i, W_c, W_o are the weight matrices, b_f, b_i, b_c, b_o are the bias matrices, and σ is the Sigmoid function, that is, $\sigma = (1/1 + e^{-x})$; its value is in the interval $(0, 1)$. $\circ$ is Hadamard product, that is, the multiplication of corresponding elements of the two same order matrices. It should be noted that LSTM has a multilayer structure, which can approximate unknown nonlinearities, and it has a small amount of computation. It has been successfully applied in many fields such as image processing, voice recognition, natural language processing, information extraction, and trend prediction [44–46, 48].

Lemma 2 (see [46]). The unknown continuous functions can be approximated with the help of LSTM network. It is shown that for any given continuous function $F_Z: \mathbb{R}^n \rightarrow \mathbb{R}$ on a compact set $M \in \mathbb{R}^n$ with an arbitrary $\varsigma_Z > 0$, it can be expressed that

$$F_Z = \hat{O}_Z \tanh(C_Z), \quad (13)$$

where $\hat{O}_Z, C_Z$ are the values of output gate and update gate in the LSTM network, respectively. In the ideal condition, the output of the LSTM network can be defined as

$$H_Z = O_Z \tanh(C_Z) + \varsigma_Z, \quad (14)$$

FIGURE 1: The structure of LSTM.

where O_Z represents the optimal output gate value and $\varsigma_Z > 0$ represents the approximation error, which is bounded and can be arbitrarily small.

Definition 1. Define a one-to-one NM $\mathfrak{R}$ [49]: $v \longrightarrow \tau$ as follows:

$$\tau = \log \frac{\ell_1 + v}{\ell_2 - v}, \quad (15)$$

where $\mathfrak{R}$ is a continuous elementary function. It follows from (15) that

$$v = \mathfrak{R}^{-1} = \ell_2 - \frac{\ell_1 + \ell_2}{e^\tau + 1}, \quad (16)$$

$$dv = \frac{(\ell_1 + \ell_2)e^\tau}{(e^\tau + 1)^2} d\tau.$$

3. Main Results

Considering the different time scales of attitude angle and angular velocity of fixed-wing UAV, the controller design will be divided into inner loop and outer loop, respectively. In the inner loop, the NM method is used to constrain the state errors into the predefined boundaries. In the view of the aerodynamics uncertainties, the LSTM network is introduced to approximate the unknown nonlinear functions. Considering the structural uncertainties, an adaptive law is devised. Meanwhile, in the outer loop, a new adaptive control law is designed to deal with the input uncertainties, and LSTM network is introduced to handle the nonlinearities once more. The structure of the proposed LSTM-based control method is depicted in Figure 2.

3.1. LSTM-Based Inner-Loop Output-Constrained Controller Design. Define the desired trajectories of attitude angles are $\theta_d = [\vartheta_d, \psi_d, \gamma_d]^T$, define $e_{1,\vartheta} = \vartheta - \vartheta_d$, $e_{1,\psi} = \psi - \psi_d$, $e_{1,\gamma} = \gamma - \gamma_d$, and they represent the tracking error in three directions. Therefore, the inner loop error $e_1 = [e_{1,\vartheta}, e_{1,\psi}, e_{1,\gamma}]^T$ can be obtained as

$$\dot{e}_1 = A_\theta \Omega_\theta \omega + f(\theta) + d_\theta(t) - \dot{\theta}_d, \quad (17)$$

where $\Omega_\theta = ((A_\theta + \Delta A_\theta)/A_\theta)$.

In order to carry out state constraints, we introduce the following one-to-one NM in the inner loop:

$$s_\vartheta = \log \frac{\ell_{a,1} + e_{1,\vartheta}}{\ell_{a,2} - e_{1,\vartheta}},$$

$$s_\psi = \log \frac{\ell_{b,1} + e_{1,\psi}}{\ell_{b,2} - e_{1,\psi}}, \quad (18)$$

$$s_\gamma = \log \frac{\ell_{c,1} + e_{1,\gamma}}{\ell_{c,2} - e_{1,\gamma}}.$$

Define $s_\theta = [s_\vartheta, s_\psi, s_\gamma]^T$. According to Definition 1, it is easy to obtain that its inverse mapping is

$$e_{1,\vartheta} = \ell_{a,2} - \frac{\ell_{a,1} + \ell_{a,2}}{e^{s_\vartheta} + 1},$$

$$e_{1,\psi} = \ell_{b,2} - \frac{\ell_{b,1} + \ell_{b,2}}{e^{s_\psi} + 1}, \quad (19)$$

$$e_{1,\gamma} = \ell_{c,2} - \frac{\ell_{c,1} + \ell_{c,2}}{e^{s_\gamma} + 1},$$

FIGURE 2: The structure of the proposed control scheme.

where $\ell_{a,1}, -\ell_{a,2}, \ell_{b,1}, -\ell_{b,2}$, and $\ell_{c,1}, -\ell_{c,2}$ are predefined boundaries of $e_{1,\vartheta}, e_{1,\psi}$, and $e_{1,\gamma}$. Thus, all the attitude tracking errors are retained in the open sets $\Pi_\theta = \{\theta: -\ell_2 < \theta < \ell_1\}$. Hence, we get that

$$\dot{s}_\theta = \text{Diag} \left[\frac{e^{s_\vartheta} + e^{-s_\vartheta} + 2}{\ell_{a,1} + \ell_{a,2}} \frac{e^{s_\psi} + e^{-s_\psi} + 2}{\ell_{b,1} + \ell_{b,2}} \frac{e^{s_\gamma} + e^{-s_\gamma} + 2}{\ell_{c,1} + \ell_{c,2}} \right] \dot{e}_1 = M_1(\theta) \dot{e}_1, \quad (20)$$

where $M_1(\theta)$ represents the transformation matrix.

Thus, the differential of inner loop error (17) can be transformed into

$$\dot{s}_\theta = M_1(\theta) (A_\theta \Omega_\theta \omega + f(\theta) + d_\theta(t) - \dot{\theta}_d). \quad (21)$$

According to Lemma 2, in view of the uncertainty of $f(\theta) \in \mathbb{R}^{3 \times 1}$, we introduce a LSTM network $O_{t,\theta}^\circ \tanh(C_{t,\theta})$. Let $\hat{O}_{t,\theta}$ be the estimated value of $O_{t,\theta}$. Then, $f(\theta) = O_{t,\theta}^\circ \tanh(C_{t,\theta}) + \varepsilon_\theta$, where ε_θ is the bounded approximation error. Define $\xi_\theta = \sup_{t \geq 0} \|\varepsilon_\theta + d_\theta(t)\|$. Simultaneously, let $\hat{\xi}_\theta$ be the estimations of ξ_θ . Note that $\hat{\xi}_\theta$ is updated by adaptive law.

According to (21), the indirect virtual control signal is obtained as

$$\omega_{vc} = A_\theta^{-1} \left(-\frac{k_1 s_\theta}{M_1(\theta)} - \hat{O}_{t,\theta}^\circ \tanh(C_{t,\theta}) - \hat{\xi}_\theta \varphi(\theta) + \dot{\theta}_d \right), \quad (22)$$

$$\varphi(\theta) = \frac{\Sigma_1^T(\theta)}{\sqrt{\Sigma_1(\theta) \Sigma_1^T(\theta) + \varepsilon_{\xi,\Sigma}^2}}, \quad \forall \varepsilon_{\xi,\Sigma} > 0,$$

where $k_1 \in \mathbb{R}^{3 \times 3}$ is the control gain of the inner loop and $\Sigma_1(\theta) = (s_\theta^T s_\theta) s_\theta^T M_1(\theta) \in \mathbb{R}^{1 \times 3}$. It is easy to know that due to the influence of unknown term ΔA_θ , it cannot guarantee the stability of the inner loop system only using the control signal ω_{vc} , so we define the final virtual control signal in the inner loop as ω_v , which is designed as

$$\omega_v = \omega_{va} + \omega_{vc}, \quad (23)$$

where $\omega_{va} \in \mathbb{R}^{3 \times 1}$ is an adaptive compensation term of the input uncertainty, which is designed as

$$\omega_{va} = -\hat{\Psi}_{1,\theta} \omega_{vc}, \quad (24)$$

where $\hat{\Psi}_{1,\theta}$ is the estimate of $\Psi_{1,\theta}$, $\Psi_{1,\theta} = ((\Omega_\theta - I_3)/\Omega_\theta) \in \mathbb{R}^{3 \times 3}$. By substituting (22) and (23) into (21), we can get that

$$\dot{s}_\theta = -k_1 s_\theta + M_1(\theta)(A\Omega_\theta e_2 - A\Omega_\theta \tilde{\Psi}_{1,\theta} \omega_c - \tilde{O}_{t,\theta} \circ \tanh(C_{t,\theta}) + \varepsilon_\theta + d_\theta(t) - \hat{\xi}_\theta \varphi(\theta)), \quad (25)$$

where $e_2 = \omega - \omega_v$. In order to analyze the stability of the system, we construct the following Lyapunov function as

$$V_1 = \frac{1}{4}(s_\theta^T s_\theta)^2 + \frac{1}{2\Gamma_{\tilde{O}_{t,\theta}}} \tilde{O}_{t,\theta}^T \tilde{O}_{t,\theta} + \frac{1}{2\Gamma_{\tilde{\xi}_\theta}} \tilde{\xi}_\theta^2 + \frac{1}{2\Gamma_{\tilde{\Psi}_{1,\theta}}} \text{Tr}(\tilde{\Psi}_{1,\theta}^T \Omega_1 \tilde{\Psi}_{1,\theta}), \quad (26)$$

where $\tilde{\Psi}_{1,\theta} = \tilde{\Psi}_{1,\theta} - \Psi_{1,\theta}$, $\tilde{O}_{t,\theta} = \hat{O}_{t,\theta} - O_{t,\theta}$, $\tilde{\xi}_\theta = \hat{\xi}_\theta - \xi_\theta$, and $\Gamma_{\tilde{O}_{t,\theta}}, \Gamma_{\tilde{\xi}_\theta}, \Gamma_{\tilde{\Psi}_{1,\theta}} > 0$ is the adaptive gain. $\text{Tr}(A)$ denotes the trace of matrices A . Similar to (25), we can take the differential of V_1 as

$$\dot{V}_1 = (s_\theta^T s_\theta) s_\theta^T \dot{s}_\theta + \frac{1}{\Gamma_{\tilde{O}_{t,\theta}}} \tilde{O}_{t,\theta}^T \dot{\tilde{O}}_{t,\theta} + \frac{1}{\Gamma_{\tilde{\xi}_\theta}} \tilde{\xi}_\theta \dot{\tilde{\xi}}_\theta + \frac{1}{\Gamma_{\tilde{\Psi}_{1,\theta}}} \text{Tr}(\tilde{\Psi}_{1,\theta}^T \Omega_1 \dot{\tilde{\Psi}}_{1,\theta}). \quad (27)$$

By substituting (25) into (27), we can get that

$$\begin{aligned} \dot{V}_1 = & -k_1 (s_\theta^T s_\theta)^2 + \Sigma_1(\theta)(A\Omega_\theta e_2 - A\Omega_\theta \tilde{\Psi}_{1,\theta} \omega_c - \tilde{O}_{t,\theta} \circ \tanh(C_{t,\theta}) + \varepsilon_\theta + d_\theta(t) - \hat{\xi}_\theta \varphi(\theta)) \\ & + \frac{1}{\Gamma_{\tilde{O}_{t,\theta}}} \tilde{O}_{t,\theta}^T \dot{\tilde{O}}_{t,\theta} + \frac{1}{\Gamma_{\tilde{\xi}_\theta}} \tilde{\xi}_\theta \dot{\tilde{\xi}}_\theta + \frac{1}{\Gamma_{\tilde{\Psi}_{1,\theta}}} \text{Tr}(\tilde{\Psi}_{1,\theta}^T \Omega_\theta \dot{\tilde{\Psi}}_{1,\theta}). \end{aligned} \quad (28)$$

According to Lemma 1, the following inequality can be obtained:

$$\Sigma_1(\theta)[\varepsilon_\theta + d_\theta(t)] \leq \|\Sigma_1(\theta)\| \xi_\theta \leq \frac{\xi_\theta \Sigma_1(\theta) \Sigma_1^T(\theta)}{\sqrt{\Sigma_1(\theta) \Sigma_1^T(\theta) + \varepsilon_{\xi,\Sigma}^2}}, \quad (29)$$

where $\varepsilon_{\xi,\Sigma} > 0$. Moreover, it is apparent that

$$\Sigma_1(\theta) A \Omega_\theta e_2 = \Pi_1(\theta) \Omega_\theta e_2 \leq \lambda_{\max^2}(\Omega_\theta) + \frac{1}{2} \Pi_1(\theta) \Pi_1^T(\theta) e_2 e_2^T, \quad (30)$$

where $\Pi_1(\theta) = \Sigma_1(\theta) A \in \mathbb{R}^{1 \times 3}$. Combining (28), (29), and (30), it can be proven that

$$\begin{aligned} \dot{V}_1 \leq & -k_1 (s_\theta^T s_\theta)^2 + \frac{1}{\Gamma_{\tilde{O}_{t,\theta}}} \tilde{O}_{t,\theta}^T \dot{\tilde{O}}_{t,\theta} + \frac{1}{\Gamma_{\tilde{\xi}_\theta}} \tilde{\xi}_\theta \dot{\tilde{\xi}}_\theta + \frac{1}{\Gamma_{\tilde{\Psi}_{1,\theta}}} \text{Tr}(\tilde{\Psi}_{1,\theta}^T \Omega_\theta \dot{\tilde{\Psi}}_{1,\theta}) - \Sigma_1(\theta) A \Omega_\theta \tilde{\Psi}_{1,\theta} \omega_c \\ & - \Sigma_1(\theta) \tilde{O}_{t,\theta} \circ \tanh(C_{t,\theta}) - \tilde{\xi}_\theta \Sigma_1(\theta) \varphi(\theta) + \lambda_{\max^2}(\Omega_\theta) + \frac{1}{2} \Pi_1(\theta) \Pi_1^T(\theta) e_2 e_2^T. \end{aligned} \quad (31)$$

Therefore, design the update law for $\hat{O}_{t,\theta}$, $\hat{\xi}_\theta$, $\hat{\Psi}_{1,\theta}$ as

$$\begin{aligned} \dot{\hat{O}}_{t,\theta} &= \Gamma_{\tilde{O}_{t,\theta}} (\Sigma_1(\theta)^T \circ \tanh(C_{t,\theta}) - \sigma_{O_{t,\theta}} \hat{O}_{t,\theta}), \\ \dot{\hat{\xi}}_\theta &= \Gamma_{\tilde{\xi}_\theta} (\Sigma_1(\theta) \varphi(\theta) - \sigma_{\xi_\theta} \hat{\xi}_\theta), \\ \dot{\hat{\Psi}}_{1,\theta} &= \Gamma_{\tilde{\Psi}_{1,\theta}} (\omega_c \Sigma_1(\theta) A_\theta - \sigma_{\Psi_{1,\theta}} \hat{\Psi}_{1,\theta}), \end{aligned} \quad (32)$$

where $\sigma_{O_{t,\theta}}, \sigma_{\xi_\theta}, \sigma_{\Psi_{1,\theta}} > 0$. Therefore, by using update law (32), we know that

$$\dot{V}_1 \leq -k_1(s_\theta^T s_\theta)^2 + \lambda_{\max^2}(\Omega_\theta) + \frac{1}{2}\Pi_1(\theta)\Pi_1^T(\theta)e_2e_2^T - \sigma_{O_{t,\theta}}\tilde{O}_{t,\theta}^T\hat{O}_{t,\theta} - \sigma_{\xi_\theta}\tilde{\xi}_\theta\hat{\xi}_\theta - \sigma_{\Psi_{1,\theta}}\text{Tr}(\tilde{\Psi}_{1,\theta}^T\Omega_\theta\tilde{\Psi}_{1,\theta}). \quad (33)$$

Define

$$\text{Tr}(\tilde{\Psi}_{1,\theta}^T\Omega_\theta\tilde{\Psi}_{1,\theta}) = \sum_{i=1}^3 \sum_{j=1}^3 \Omega_{\theta ii} \tilde{\Psi}_{1ij}^2 \geq \Omega_{\theta \min} \|\tilde{\Psi}_{1,\theta}\|_F^2. \quad (34)$$

According to the definition of F-norm, we can get that

$$\|\tilde{\Psi}_{1,\theta}\|_F^2 = \sum_{i=1}^3 \sum_{j=1}^3 \tilde{\Psi}_{1,\theta ij}^2, \quad (35)$$

where $\Omega_{\theta \min}$ represents the smallest diagonal element of Ω_θ .

$$\left| \text{Tr}(\tilde{\Psi}_{1,\theta}^T\Omega_\theta\Psi_{1,\theta}) \right| \leq \|\tilde{\Psi}_{1,\theta}\|_F \|\Omega_\theta\Psi_{1,\theta}\|_F \leq \|\tilde{\Psi}_{1,\theta}\|_F \|\Omega_\theta\|_F \|\Psi_{1,\theta}\|_F. \quad (36)$$

Since

$$\begin{aligned} -\sigma_{O_{t,\theta}}\tilde{O}_{t,\theta}^T\hat{O}_{t,\theta} &\leq -\frac{1}{2}\sigma_{O_{t,\theta}}\|\tilde{O}_{t,\theta}\|_F^2 + \frac{1}{2}\sigma_{O_{t,\theta}}\|O_{t,\theta}\|_F^2, \\ -\sigma_{\xi_\theta}\tilde{\xi}_\theta\hat{\xi}_\theta &\leq -\frac{1}{2}\sigma_{\xi_\theta}\|\tilde{\xi}_\theta\|_F^2 + \frac{1}{2}\sigma_{\xi_\theta}\|\xi_\theta\|_F^2. \end{aligned} \quad (37)$$

Substituting (33), (34), (36), and (37) into (33), we can rewrite (33) as

$$\begin{aligned} \dot{V}_1 &\leq -\lambda_{\min}(k_1)(s_\theta^T s_\theta)^2 + \lambda_{\max^2}(\Omega_\theta) + \frac{1}{2}\Pi_1(\theta)\Pi_1^T(\theta)e_2e_2^T - \frac{1}{2}\sigma_{O_{t,\theta}}\|\tilde{O}_{t,\theta}\|_F^2 \\ &\quad + \frac{1}{2}\sigma_{O_{t,\theta}}\|O_{t,\theta}\|_F^2 - \frac{1}{2}\sigma_{\xi_\theta}\|\tilde{\xi}_\theta\|_F^2 + \frac{1}{2}\sigma_{\xi_\theta}\|\xi_\theta\|_F^2 - \sigma_{\Psi_{1,\theta}}\Omega_{\theta \min}\|\tilde{\Psi}_{1,\theta}\|_F^2 \\ &\quad + \frac{1}{2}\sigma_{\Psi_{1,\theta}}\|\Omega_\theta\|_F(\|\tilde{\Psi}_{1,\theta}\|_F^2 + \|\Psi_{1,\theta}\|_F^2). \end{aligned} \quad (38)$$

Therefore, we can finally get that

$$\begin{aligned} \dot{V}_1 &\leq -\lambda_{\min}(k_1)\|s_\theta^T s_\theta\|^2 - \frac{1}{2}\sigma_{O_{t,\theta}}\|\tilde{O}_{t,\theta}\|_F^2 - \frac{1}{2}\sigma_{\xi_\theta}\|\tilde{\xi}_\theta\|_F^2 \sigma_{\Psi_{1,\theta}} \left(\Omega_{\theta \min} - \frac{1}{2}\|\Omega_\theta\|_F \right) \|\tilde{\Psi}_{1,\theta}\|_F^2 \\ &\quad + \frac{1}{2}\|\Pi_1(\theta)\|^2\|e_2\|^2 + \varepsilon_{\Pi 1}, \end{aligned} \quad (39)$$

where

$$\varepsilon_{\Pi 1} = \frac{1}{2}\sigma_{\xi_\theta}\|\xi_\theta\|_F^2 + \frac{1}{2}\sigma_{\Psi_{1,\theta}}\|\Omega_\theta\|_F\|\Psi_{1,\theta}\|_F^2 + \frac{1}{2}\sigma_{O_{t,\theta}}\|O_{t,\theta}\|_F^2 + \lambda_{\max^2}(\Omega_\theta) + \frac{1}{2}\|\Pi_1(\theta)\|^2\|e_2\|^2. \quad (40)$$

3.2. LSTM-Based Input Uncertainty Suppressed Outer Loop Controller Design. The aim of this part is to design an adaptive controller to guarantee the stability of outer loop. In view of (8), we can obtain

$$\dot{e}_2 = [B_\omega + \Delta B_\omega]\delta + C(\omega) + f(\theta, \omega) + d_\omega(t) - \dot{\omega}_v. \quad (41)$$

Similarly, according to Lemma 2, in view of the uncertainty of $f(\theta, \omega) \in \mathbb{R}^{3 \times 1}$, we introduce a LSTM network $O_{t,\omega} \tanh(C_{t,\omega})$. Let $\hat{O}_{t,\omega}$ be the estimated value of $O_{t,\omega}$. Then,

$f(\theta, \omega) = O_{t,\omega} \circ \tanh(C_{t,\omega}) + \varepsilon_\omega$, where ε_ω is the bounded approximation error. Define $\xi_\omega = \sup_{t \geq 0} \|\varepsilon_\omega + d_\omega(t)\|$. Simultaneously, let $\hat{\xi}_\omega$ be the estimations of ξ_ω . Note that $\hat{\xi}_\omega$ is updated by adaptive law.

According to (41), the indirect rudder deviation control signal is designed as

$$\begin{aligned} \delta_{vc} &= B_\omega^{-1} \left(-k_2 e_2 - \frac{1}{2} \|\Pi_1(\theta)\|^2 e_2 - C(\omega) - \hat{O}_{t,\omega} \circ \tanh(C_{t,\omega}) - \hat{\xi}_\omega \varphi(e_2) + \underline{\omega}_v \right), \\ \varphi(e_2) &= \frac{e_2}{\sqrt{e_2^T e_2 + \varepsilon_{\xi, e_2}^2}}, \quad \forall \varepsilon_{\xi, e_2} > 0, \end{aligned} \quad (42)$$

where $k_2 \in \mathbb{R}^{3 \times 3}$ is the control gain of outer loop and $B_\omega \in \mathbb{R}^{3 \times 5}$. Hence, with the aid of the definition of generalized inverse, we can define that $B_\omega^{-1} = (B_\omega^T / B_\omega B_\omega^T)$. According to (41), it is easy to know that due to the influence of uncertainty term ΔB_ω , it cannot guarantee the stability of the outer loop system only using the control signal δ_{vc} , so we define the final virtual control signal of outer loop as δ_v , which is designed as

$$\delta_v = \delta_{va} + \delta_{vc}, \quad (43)$$

where $\delta_{va} \in \mathbb{R}^{5 \times 1}$ is an adaptive compensation term of the input uncertainty, which is designed as

$$\delta_{va} = -\hat{\Psi}_{2,\omega} \delta_{vc}, \quad (44)$$

where $\hat{\Psi}_{2,\omega}$ is the estimate of $\Psi_{2,\omega}$ and $\Psi_{2,\omega} = ((\Omega_\omega - I_5) / \Omega_\omega) \in \mathbb{R}^{5 \times 5}$. Substituting (42)–(44) into (41), we can get that

$$\dot{e}_2 = -k_2 e_2 - \frac{1}{2} \|\Pi_1(\theta)\|^2 e_2 - B_\omega \Omega_\omega \tilde{\Psi}_{2,\omega} \delta_{vc} - \tilde{O}_{t,\omega} \circ \tanh(C_{t,\omega}) - \hat{\xi}_\omega \varphi(e_2) + \varepsilon_\omega + d_\omega(t). \quad (45)$$

Consider the following Lyapunov function candidate:

$$V_2 = V_1 + \frac{1}{2} e_2^T e_2 + \frac{1}{2\Gamma_{\Psi_{2,\omega}}} \text{Tr} \left(\tilde{\Psi}_{2,\omega}^T \Omega_\omega \tilde{\Psi}_{2,\omega} \right) + \frac{1}{2\Gamma_{O_{t,\omega}}} \tilde{O}_{t,\omega}^T \tilde{O}_{t,\omega} + \frac{1}{2\Gamma_{\xi_\omega}} \tilde{\xi}_\omega^2, \quad (46)$$

where $\tilde{\xi}_\omega = \hat{\xi}_\omega - \xi_\omega$, $\tilde{O}_{t,\omega} = \hat{O}_{t,\omega} - O_{t,\omega}$, $\tilde{\Psi}_{2,\omega} = \hat{\Psi}_{2,\omega} - \Psi_{2,\omega}$, $\Gamma_{\xi_\omega}, \Gamma_{O_{t,\omega}}, \Gamma_{\Psi_{2,\omega}} > 0$. According to Lemma 2, we can take the differential of V_2 as

$$\begin{aligned} \dot{V}_2 &= \dot{V}_1 - \frac{1}{2} \|\Pi_1(\theta)\|^2 e_2^T e_2 - k_2 e_2^T e_2 - e_2^T B_\omega \Omega_\omega \tilde{\Psi}_{2,\omega} \delta_{vc} - e_2^T \tilde{O}_{t,\omega} \circ \tanh(C_{t,\omega}) - e_2^T \tilde{\xi}_\omega \varphi(e_2) \\ &\quad + e_2^T [\varepsilon_\omega + d_\omega(t)] + \frac{1}{\Gamma_{\Psi_{2,\omega}}} \text{Tr} \left(\tilde{\Psi}_{2,\omega}^T \Omega_\omega \dot{\tilde{\Psi}}_{2,\omega} \right) + \frac{1}{\Gamma_{O_{t,\omega}}} \tilde{O}_{t,\omega}^T \dot{\tilde{O}}_{t,\omega} + \frac{1}{\Gamma_{\xi_\omega}} \tilde{\xi}_\omega \dot{\tilde{\xi}}_\omega. \end{aligned} \quad (47)$$

According to Lemma 1, the following inequality can be obtained:

$$e_2^T [\varepsilon_\omega + d_\omega(t)] \leq \xi_\omega \|e_2\| \leq \xi_\omega e_2^T \varphi(e_2) + \xi_\omega \varepsilon_{\xi, e_2}. \quad (48)$$

By substituting (48) into (47), it can be easily obtained that

$$\begin{aligned} \dot{V}_2 \leq \dot{V}_1 - \frac{1}{2} \|\Pi_1(\theta)\|^2 e_2^T e_2 - k_2 e_2^T e_2 - e_2^T B_\omega \Omega_\omega \tilde{\Psi}_{2,\omega} \delta_{vc} - e_2^T \tilde{O}_{t,\omega} \tanh(C_{t,\omega}) - e_2^T \tilde{\xi}_\omega \varphi(e_2) + \xi_\omega \varepsilon_{\xi, e_2} \\ + \frac{1}{\Gamma_{\Psi_{2,\omega}}} \text{Tr} \left(\tilde{\Psi}_{2,\omega}^T \Omega_\omega \dot{\tilde{\Psi}}_{2,\omega} \right) + \frac{1}{\Gamma_{O_{t,\omega}}} \tilde{O}_{t,\omega}^T \dot{\tilde{O}}_{t,\omega} + \frac{1}{\Gamma_{\xi_\omega}} \tilde{\xi}_\omega^T \dot{\tilde{\xi}}_\omega. \end{aligned} \quad (49)$$

In view of (49), the update laws for $\tilde{\Psi}_{2,\omega}$, $\tilde{O}_{t,\omega}$, $\tilde{\xi}_\omega$ can be designed as follows:

$$\begin{aligned} \dot{\tilde{\Psi}}_{2,\omega} &= \Gamma_{\Psi_{2,\omega}} (\delta_{vc} e_2^T B_\omega - \sigma_{\Psi_{2,\omega}} \tilde{\Psi}_{2,\omega}), \\ \dot{\tilde{O}}_{t,\omega} &= \Gamma_{O_{t,\omega}} (e_2 \circ \tanh(C_{t,\omega}) - \sigma_{O_{t,\omega}} \tilde{O}_{t,\omega}), \\ \dot{\tilde{\xi}}_\omega &= \Gamma_{\xi_\omega} (e_2^T \varphi(e_2) - \sigma_{\xi_\omega} \tilde{\xi}_\omega), \end{aligned} \quad (50)$$

where $\sigma_{\Psi_{2,\omega}}, \sigma_{O_{t,\omega}}, \sigma_{\xi_\omega} > 0$.

By combining the (49) with (50), we can obtain that

$$\dot{V}_2 \leq \dot{V}_1 - \frac{1}{2} \|\Pi_1(\theta)\|^2 e_2^T e_2 - k_2 e_2^T e_2 - \sigma_{\Psi_{2,\omega}} \text{Tr} \left(\tilde{\Psi}_{2,\omega}^T \Omega_\omega \tilde{\Psi}_{2,\omega} \right) - \sigma_{O_{t,\omega}} \tilde{O}_{t,\omega}^T \tilde{O}_{t,\omega} - \sigma_{\xi_\omega} \tilde{\xi}_\omega^T \tilde{\xi}_\omega + \xi_\omega \varepsilon_{\xi, e_2}. \quad (51)$$

Similarly, we can get that

$$\begin{aligned} \dot{V}_2 \leq \dot{V}_1 - \frac{1}{2} \|\Pi_1(\theta)\|^2 \|e_2\|^2 - \lambda_{\min}(k_2) \|e_2\|^2 - \frac{1}{2} \sigma_{O_{t,\omega}} \|\tilde{O}_{t,\omega}\|_F^2 + \frac{1}{2} \sigma_{O_{t,\omega}} \|O_{t,\omega}\|_F^2 - \frac{1}{2} \sigma_{\xi_\omega} \|\tilde{\xi}_\omega\|_F^2 \\ + \frac{1}{2} \sigma_{\xi_\omega} \|\xi_\omega\|_F^2 - \sigma_{\Psi_{2,\omega}} \Omega_\omega \min \|\tilde{\Psi}_{2,\omega}\|_F^2 + \frac{1}{2} \sigma_{\Psi_{2,\omega}} \|\Omega_\omega\|_F \left(\|\tilde{\Psi}_{2,\omega}\|_F^2 + \|\Psi_{2,\omega}\|_F^2 \right) + \xi_\omega \varepsilon_{\xi, e_2}. \end{aligned} \quad (52)$$

Substituting (39) into (52), we can finally get that

$$\begin{aligned} \dot{V}_2 \leq -\lambda_{\min}(k_1) \|s_\theta^T s_\theta\|^2 - \frac{1}{2} \sigma_{O_{t,\theta}} \|\tilde{O}_{t,\theta}\|_F^2 - \frac{1}{2} \sigma_{\xi_\theta} \|\tilde{\xi}_\theta\|_F^2 - \sigma_{\Psi_{1,\theta}} \left(\Omega_{\theta \min} - \frac{1}{2} \|\Omega_\theta\|_F \right) \|\tilde{\Psi}_{1,\theta}\|_F^2 \\ - \lambda_{\min}(k_2) \|e_2\|^2 - \frac{1}{2} \sigma_{O_{t,\omega}} \|\tilde{O}_{t,\omega}\|_F^2 - \frac{1}{2} \sigma_{\xi_\omega} \|\tilde{\xi}_\omega\|_F^2 - \sigma_{\Psi_{2,\omega}} \left(\Omega_{\omega \min} - \frac{1}{2} \|\Omega_\omega\|_F \right) \|\tilde{\Psi}_{2,\omega}\|_F^2 + \varepsilon_{\Pi 2}, \end{aligned} \quad (53)$$

where

$$\varepsilon_{\Pi 2} = \varepsilon_{\Pi 1} + \frac{1}{2} \sigma_{O_{t,\omega}} \|O_{t,\omega}\|_F^2 + \frac{1}{2} \sigma_{\xi_\omega} \|\xi_\omega\|_F^2 + \frac{1}{2} \sigma_{\Psi_{2,\omega}} \|\Omega_\omega\|_F \|\Psi_{2,\omega}\|_F^2 + \xi_\omega \varepsilon_{\xi, e_2}. \quad (54)$$

3.3. Stability Analysis. The main result on global adaptive tracking is stated in this section.

Theorem 1. Consider the closed-loop system consisting of the interconnected system (8), the controller ((22), (23), (42), and

(43)), and the adaptive update laws (30) and (50). Suppose Assumptions 1–5 are satisfied. Moreover, it is guaranteed that the signals are bounded and the state can track the desired

signal θ_d accurately in the presence of the changing uncertainties and unknown disturbance.

Proof. According to inequality (53),

$$\begin{aligned} \dot{V}_2 \leq & -\lambda_{\min}(k_1) \|s_\theta^T s_\theta\|^2 - \frac{1}{2} \sigma_{O_{t,\theta}} \|\tilde{O}_{t,\theta}\|_F^2 - \frac{1}{2} \sigma_{\xi_\theta} \|\tilde{\xi}_\theta\|_F^2 - \sigma_{\Psi_{1,\theta}} \left(\Omega_{\theta\min} - \frac{1}{2} \|\Omega_\theta\|_F \right) \|\tilde{\Psi}_{1,\theta}\|_F^2 \\ & - \lambda_{\min}(k_2) \|e_2\|^2 - \frac{1}{2} \sigma_{O_{t,\omega}} \|\tilde{O}_{t,\omega}\|_F^2 - \frac{1}{2} \sigma_{\xi_\omega} \|\tilde{\xi}_\omega\|_F^2 - \sigma_{\Psi_{2,\omega}} \left(\Omega_{\omega\min} - \frac{1}{2} \|\Omega_\omega\|_F \right) \|\tilde{\Psi}_{2,\omega}\|_F^2 + \varepsilon_{\Pi 2}. \end{aligned} \quad (55)$$

Define

$$\begin{aligned} c_2 = \min & \left\{ \begin{array}{l} 2\lambda_{\min}(k_1), 2\lambda_{\min}(k_2), \Gamma_{\xi_\theta} \sigma_{\xi_\theta}, \Gamma_{\xi_\omega} \sigma_{\xi_\omega}, \Gamma_{O_{t,\theta}} \sigma_{O_{t,\theta}}, \Gamma_{O_{t,\omega}} \sigma_{O_{t,\omega}}, \\ 2\Gamma_{\Psi_{1,\theta}} \sigma_{\Psi_{1,\theta}} \left(\Omega_{\theta\min} - \frac{1}{2} \|\Omega_\theta\|_F \right), 2\Gamma_{\Psi_{2,\omega}} \sigma_{\Psi_{2,\omega}} \left(\Omega_{\omega\min} - \frac{1}{2} \|\Omega_\omega\|_F \right) \end{array} \right\}, \\ \varepsilon_y = \sup_{t \geq 0} & |\varepsilon_{\Pi 2}|. \end{aligned} \quad (56)$$

We can obtain that

$$\dot{V}_2 \leq -c_2 V_2 + \varepsilon_y. \quad (57)$$

By solving (57), we can get that

$$0 \leq V_2 \leq \left(V_2(0) - \frac{\varepsilon_y}{c_2} \right) e^{-c_2 t} + \frac{\varepsilon_y}{c_2} \quad \forall t \geq 0. \quad (58)$$

Thus, from the Lyapunov function V_2 and (58), we can obviously get that $0 \leq V_2 \leq \max\{V_2(0), (\varepsilon_y/c_2)\}$ holds for all $t \geq 0$. Hence, $s_\theta, e_2, \tilde{\xi}_\theta, \tilde{O}_{t,\theta}, \tilde{\Psi}_{1,\theta}, \tilde{\xi}_\omega, \tilde{O}_{t,\omega}, \tilde{\Psi}_{2,\omega}$ can be all guaranteed as bounded signals. Considering $\tilde{\xi}_\theta = \tilde{\xi}_\theta + \xi_\theta, \tilde{O}_{t,\theta} = \tilde{O}_{t,\theta} + O_{t,\theta}, \tilde{\Psi}_{1,\theta} = \tilde{\Psi}_{1,\theta} + \Psi_{1,\theta}, \tilde{\xi}_\omega = \tilde{\xi}_\omega + \xi_\omega, \tilde{O}_{t,\omega} = \tilde{O}_{t,\omega} + O_{t,\omega}, \tilde{\Psi}_{2,\omega} = \tilde{\Psi}_{2,\omega} + \Psi_{2,\omega}$, we can arrive at the conclusion that $\tilde{\xi}_\theta, \tilde{O}_{t,\theta}, \tilde{\Psi}_{1,\theta}, \tilde{\xi}_\omega, \tilde{O}_{t,\omega}, \tilde{\Psi}_{2,\omega}$ are also all bounded signals. It can be concluded from (22), (23), (42), and (43) that all the signals are guaranteed to be uniformly ultimately bounded. Further, considering the one-to-one NM (18), it can be found that the error signals $e_\vartheta, e_\psi, e_\gamma$ are also limited to a compact set. The proof is completed. $\square$

4. Simulations

In this part, to verify the effectiveness of the proposed control method based on LSTM for fixed-wing UAVs, four cases of numerical examples based on the mathematical model described by (8) are carried out. For comparison, the SMC method [6], DOBC-based method [42], and RBFNN control method [40] are employed.

It is assumed that the UAV flight height is $h = 1000\text{m}$, and the initial attitude angles are $\vartheta = \psi = \gamma = 0\text{ rad}$, respectively. The initial attitude angular velocities are $\omega_z = \omega_y = \omega_x = 0\text{ (rad/s)}$, respectively. Meanwhile, the square wave is selected as the expected signal, which can be described as

$$\begin{aligned} \vartheta_d &= \begin{cases} 20, & 0 \leq t \leq \frac{T}{2}, \\ -20, & 0 < t \leq T, \end{cases} \\ \psi_d &= \begin{cases} 15, & 0 \leq t \leq \frac{T}{2}, \\ -15, & 0 < t \leq T, \end{cases} \\ \gamma_d &= \begin{cases} 10, & 0 \leq t \leq \frac{T}{2}, \\ -10, & 0 < t \leq T, \end{cases} \end{aligned} \quad (59)$$

where T is the simulation time and $T = 20\text{ s}$.

In this simulation, the parameters of the fixed-wing UAV are selected as listed in Table 1; the aerodynamic parameters of the fixed-wing UAV are given in Table 2. The control parameters of the proposed control method are chosen as listed in Table 3. The external disturbances of inner loop and outer loop are set as $\xi_\theta = [0.06, 0.02, 0.03]^T, \xi_\omega = [0.07, 0.01, 0.04]^T$. The constrained boundary of three channels can be set as $\ell_{a,1} = \ell_{a,2} = 2, \ell_{b,1} = \ell_{b,2} = 1, \ell_{c,1} = \ell_{c,2} = 0.5$. Simultaneously, the nonlinear

TABLE 1: The parameters of the fixed-wing UAV.

$V = 10 \text{ m/s}$	$m = 28 \text{ kg}$	$b = 3.1 \text{ m}$
$c = 0.58 \text{ m}$	$S = 1.8 \text{ m}^2$	$\rho = 1.29 \text{ kg/m}^3$
$I_{xx} = 2.56 \text{ kg} \cdot \text{m}^2$	$I_{yy} = 10.9 \text{ kg} \cdot \text{m}^2$	$I_{zz} = 11.3 \text{ kg} \cdot \text{m}^2$
$I_{zx} = 0.5 \text{ kg} \cdot \text{m}^2$	$I_{xz} = 0.5 \text{ kg} \cdot \text{m}^2$	

TABLE 2: The aerodynamic parameters of the fixed-wing UAV.

Symbol	Value
$C_z^{\delta_{a1}}$	0.272
$C_z^{\delta_{a2}}$	0.272
$C_z^{\delta_{b1}}$	0.038
$C_z^{\delta_{b2}}$	0.038
C_{z0}	-0.09
$C_y^{\delta_y}$	0.053
$C_{z\alpha}$	-3.25
$C_{y\beta}$	-0.38
$C_x^{\delta_{a1}}$	-0.05
$C_x^{\delta_{a2}}$	0.05
$C_x^{\delta_{b1}}$	-0.03
$C_x^{\delta_{b2}}$	0.03
C_z^α	-0.09
C_y^β	0.087
C_x^β	0.087

TABLE 3: The control parameters of the proposed controller.

	Location	Values of the parameters
The control gains	Equations (22) and (42)	$k_1 = 10, k_2 = 20$ $\Gamma_{O_{t,\theta}} = 5, \Gamma_{\Psi_{1,\theta}} = \Gamma_{\xi_\theta} = 10$
The parameters of adaptive laws	Equations (32) and (50)	$\Gamma_{O_{t,\omega}} = 15, \Gamma_{\Psi_{2,\omega}} = \Gamma_{\xi_\omega} = 10$ $\sigma_{O_{t,\theta}} = 0.1, \sigma_{\Psi_{1,\theta}} = 0.3, \sigma_{\xi_\theta} = 0.5$ $\sigma_{O_{t,\omega}} = 0.1, \sigma_{\Psi_{2,\omega}} = 0.3, \sigma_{\xi_\omega} = 0.5$
The initial value of the adaptive gains	Equations (32) and (50)	$\hat{O}_{t,\theta}(0) = 0^{3 \times 1}, \hat{\Psi}_{1,\theta}(0) = 0^{3 \times 3}, \hat{\xi}_\theta(0) = 0$ $\hat{O}_{t,\omega}(0) = 0^{3 \times 1}, \hat{\Psi}_{2,\omega}(0) = 0^{5 \times 5}, \hat{\xi}_\omega(0) = 0$

FIGURE 3: The trajectories of ϑ with the four methods.

FIGURE 4: The trajectories of ψ with the four methods.

FIGURE 5: The trajectories of γ angle with the four methods.

FIGURE 6: The tracking error of θ with the proposed method. FIGURE 7: The tracking error of ψ with the proposed method. FIGURE 8: The tracking error of γ with the proposed method.

FIGURE 9: Rudder deviation signal with the proposed method.

FIGURE 10: The inner loop adaptive parameter change with the proposed method.

FIGURE 11: The outer loop adaptive parameter change with the proposed method.

uncertainties for the control system of the four cases are considered, which are

$$\begin{aligned}
 \Delta A_\theta &= \begin{bmatrix} 0 & 0 & 0 \\ 0 & 0 & 0 \\ 0.5 & 0.5 & 0.5 \end{bmatrix}, \\
 \Delta B_\omega &= \begin{bmatrix} 0.1 & 0 & 0 & 0 & 0 \\ 0.2 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0.3 \end{bmatrix}, \\
 f(\theta) &= \begin{bmatrix} 0.002 + 0.003\sin(6.28/10 \times t), \\ 0.001 + 0.002\sin(6.28/10 \times t), \\ 0.002 + 0.001\sin(6.28/10 \times t) \end{bmatrix}^T, \\
 f(\theta, \omega) &= \begin{bmatrix} 0.007 + 0.6\sin(6.28/10 \times t), \\ 0.001 + 0.2\sin(6.28/10 \times t), \\ 0.004 + 0.3\sin(6.28/10 \times t) \end{bmatrix}^T.
 \end{aligned} \tag{60}$$

In this paper, the LSTM networks' parameter values of the forgotten gate, the input gate, the update gate, and the output gate are chosen as $W_{fi} = 0.1, W_{ii} = 0.1, W_{ci} = 1, W_{oi} = 1, b_{fi} = b_{ii} = b_{ci} = b_{oi} = 2$ in the inner loop, and $W_{fo} = 0.1, W_{io} = 0.1, W_{co} = 1, W_{oo} = 1, b_{fo} = 2, b_{io} = 5, b_{co} = 10, b_{oo} = 12$ in the outer loop.

According to the analysis in Section 4, the simulation results are given in Figures 3 ~ 8. The tracking performance with four control methods is given in Figures 3 ~ 5. Obviously, the proposed controller can achieve satisfactory performance in the presence of the unknown disturbances

and the time-accumulating uncertainties. Although the desired signals are time-varying, the system output can track the desired signals accurately. We can only find the apparent tracking errors near $T = 10$ s. However, through a short period of time, the tracking errors are forced to converge to a small vicinity of zero quickly. On the contrary, the DOBC brings larger tracking error than that of the proposed method near the switching instant of the desired signal. Meanwhile, the trajectory of γ shows conspicuous chattering phenomenon with the DOBC method. Then, the SMC-based scheme induces unsatisfactory large overshoot, namely, this method cannot control the system at all. Finally, the RBFNN-based method cannot control the unknown disturbances timely, whose slight tremor has not been stabilized. Hence, it can be verified that satisfactory control performance can be achieved and it is clear that the output constraints can be ensured from Figures 6 ~ 8. The rudder deviation signal based on the proposed method is shown in Figure 9. Meanwhile, the adaptive parameters are demonstrated in Figures 10 and 11; it can be seen that the boundness of all the adaptive parameters can be guaranteed. Hence, it can be concluded that the introduction of the LSTM method has a favorable control performance in the presence of the high dynamic disturbances and the fault actuators.

5. Conclusion

The main contribution in this paper is to design an adaptive fault-tolerant controller based on the LSTM method for the fixed-wing UAVs in the presence of the high dynamic disturbances and the actuator faults. The adaptive laws are properly designed to handle the high dynamic disturbances and actuator faults. By introducing LSTM network, the unknown and time-accumulating nonlinearities can be approximated accurately. Moreover, the one-to-one NM method is employed to solve the output-constrained control problem. By using the Lyapunov functions, the closed-loop system is proved to be exponentially convergent. Finally, numerical simulation results demonstrate that the proposed method can provide stable and rapid attitude control performance by comparison. Furthermore, in the future, the results of this paper can be applied to other nonlinear strong disturbance problems for the fixed-wing UAVs.

Data Availability

The data used to support the findings of this study are included within the article.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

Acknowledgments

This study was supported in part by the National Natural Science Foundation of China (grant nos. 61473226 and 61503302) and the Basic Research Program of Natural

Science of Shaanxi Province (grant no. 2019ZY-CXPT-03-02).

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